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Speed Estimation of Walking and Running Using a Wearable Accelerometer Device

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Abstract

Recently, wearable devices on human activity sensing have become increasingly popular.In this paper, we propose a new method for walking and running speed estimation. A wearable device based on a tri-axial accelerometer is fixed on the chest to record the acceleration data of human body. Using the acceleration data, we design a fuzzy inference system (FIS) to determine whether the subject is motionless or locomotor. If the subject is walking or running, artificial neural networks (ANNs) are then used to estimate the speed. To validate the performance of the proposed method, we test accelerometer data collected from 3 subjects walking and running on the treadmill at different speed. The result shows good agreement between actual and estimated speed, the average accuracy is 97.78% for walking and 97.36% for running.

Keywords

Tri-axial Accelerometer; Fuzzy Inference System; Artificial Neural Network; Speed Estimation

Introduction

Speed estimation of walking and running is an important issue in areas such as physical exercise, health evaluation and rehabilitation training. Nowadays, people are increasingly concerned about health and fitness, which puts forward higher request to the accuracy and convenience of speed estimation. Although GNSS has been widely used in pedestrian navigation system (PNS), the result is not satisfactory for indoor application.Accelerometry has become a promising technique for detecting the movement of the body and estimating the energy expenditure because of some advantages such as small size, relatively low cost and measuring with minimal discomfort to the subjects (Westerterp,1999).Therefore, many methods are proposed using accelerometer data for speed estimation of walking and running. Aminian et al. (Aminian et al.,1995) proposed a walking speed estimation algorithm using a three-layer artificial neural networks (ANNs) with 4 acceleration measurements as inputs. In their study, the accelerometers were placed on the back trunk and the heel, and the first ANN generated the incline estimation while the second ANN estimated the walking speed. They trained the ANNs using treadmill data independently for each subject and applied to overground walking data. The maximum of speed-predicted error was 16% in their study. Sabatini et al. (Sabatini et al.,2005) proposed a direct integration method to obtain walking speed. They used an inertial measurement unit (IMU) fixed on the instep of the foot. The angular velocity data collected by the gyroscope was used to detect the foot flat (FF) event and the acceleration data was integrated to estimate speed using zero velocity update (ZUPT) algorithm. Their method achieved an overall RMSE of0.18 km/h based on the treadmill walking experiments at various speed ranging from 3 km/h to 6 km/h. Renaudin et al. (Renaudin et al.,2012) proposed a linear method for estimating human step lengthusing step frequency and heightwith a set of three parameters. Then the distance and average speed can be easily estimated. Their result showed an error between 2.5 and 5% of the travelled distance.

Although there have been many approaches of using accelerometry for walking and running speed estimation, limits still exist in their work. Most studies do not have a human activity recognition system, which means they can’t tell when the subject is walking or running, making it difficult to be applied in daily life. Some of their work use more than one accelerometer fixed on different parts of body, making it very uncomfortable for the subject to walk and run. Some people built simple models to estimate step length using parameters such as step

frequencyand user's height, however, as we don't know the exact relationship between step length and these step parameters, these models had their intrinsic disadvantages.In this paper, we proposed a new method for walking and running speed estimation. We used a tri-axial accelerometer fixed on the chest to collect acceleration data. A fuzzy inference system (FIS) was designed for human activity recognition. If the subject was walkingor running, ANNs were then used to estimate the speed. The whole system structure is shown in FIG. 1.

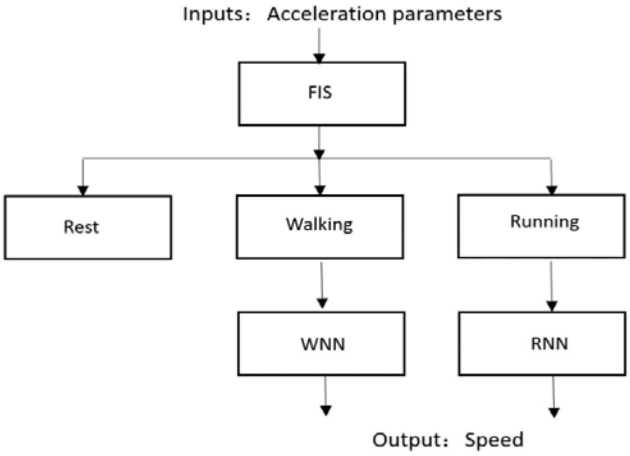


FIG. 1 WHOLE SYSTEM STRUCTURE. FIS: FUZZY INFERENCE SYSTEM, WNN: WALKING NEURAL NETWORK, RNN: RUNNING NEURAL NETWORK

Data CollectionAndPreprocessing

The assumed application scenario is estimating speed of walking or running in real-time way. Here real-time means when estimating, only short term data until now is used. The system shown in FIG. 2 consists of a wearable sensor unit, a communication gateway and a mobile phone.

The sensor unit contains a tri-axial accelerometer, ADXL345 from Analog Devices Inc. The sample rate is 100Hz, the sampling resolution is 8 bits, and the measurement range is set to ±4g. The sensor unit is fixed on the chest. A micro-controller and a bluetooth module are also included in the sensor unit for data transmission to the mobile phone. Data processing, activity recognition and speed estimating are then completed in the mobile phone.

To estimating speed in real-time way, the acceleration signal samples are segmented into window series and only nearest 100 samples are used for each window. The number 100 means time window length is one second, which is enough to include one typical movement cycle such as one walking step. As the raw data is polluted by the sensor noises, a 4-order band-pass IIR filter is designed and the cutoff frequency is set to 0.5Hz-5Hz. Thus, after filtering, noises and disturbance are almost eliminated. Then motion acceleration parameters can be extracted for the activity recognition and speed estimation.And the update cycle time is one second.

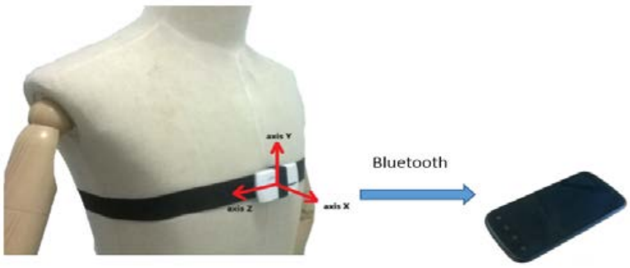


FIG. 2 DATA COLLECTION SYSTEM AND AXIS DEFINITION

Activity Recognition Using Fuzzy Inference System

To estimate the speed of walking and running, it's important to determine whether the subject is locomotor or not. Thus, an activity recognition system is necessary to be built. Using acceleration data from only one accelerometer for physical activity recognition is of great difficulty because the signal couldn't reflect the whole body movement. Although we can extract many parameters of the acceleration signal, we don't know how to use them to make

activity recognition because they are not so intuitive.

Zadeh, the founder of fuzzy sets theory, once put it, "As the complexity of a system increases, our ability to make precise and yet significant statements about its behavior diminishes until a threshold is reached beyond which the precise and significance become mutually exclusive characteristics (Zadeh,1973)." The fuzzy inference system is a good way to solve ill-defined decision-making problems because of its capability of incorporating a priori qualitative knowledge and expertise about system behavior and dynamics. In this paper, we design a fuzzy inference system to determine if the subject's activity is rest, walking, or running.

Basically a fuzzy inference system is composed of five functional blocks (Jang,1993)(see FIG. 3):

- A rule base containing a number of fuzzy if-then rules;
- A database which defines the membership functions of the fuzzy sets used in the fuzzy rules;
- A decision-making unit which performs the inference operations on the rules;
- A fuzzification interface which transforms the crisp inputs into degrees of match with linguistic values;
- Adefuzzification interface which transform the fuzzy results of the inference into a crisp output.

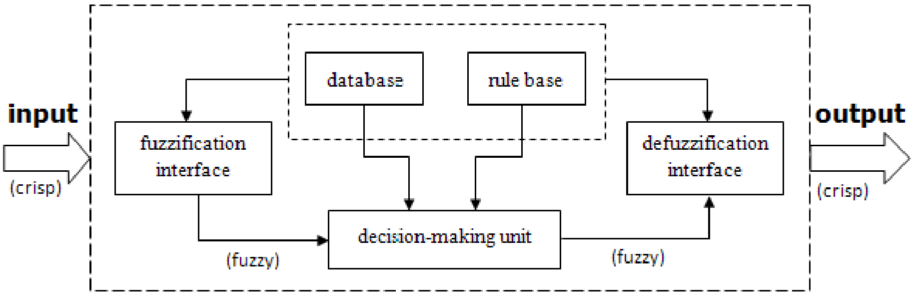


FIG. 3 STRUCTURE OF A FUZZY INFERENCE SYSTEM

We used three parameters extracted from the acceleration signal as inputs. They were peak to peak amplitude of x-axis (xPPA), standard deviation of y-axis (ySTD), and signal magnitude area (SMA). SMA is defined as follows:

$$SMA = \frac{1}{t}\int_0^t \left(|a_x(\tau)| + |a_y(\tau)| + |a_z(\tau)|\right) d\tau \tag{1}$$

Here x-axis is the frontal direction and y-axis is the vertical direction;a_x, a_y, a_z are acceleration of the three axises. Our FIS had one output named activity which determined one of the three activities: rest, walking, running. More details of FIS are as follows:

1) *Rule Base*

Fuzzy if-then rules are expressions of the form "if A then B", where A and B are called the antecedent and the consequent, respectively. In this paper, we defined four rules:

Rule 1: if SMA is low AND xPPA is low AND ySTD is low, then activity is rest.

Rule 2: if SMA is intermediate AND xPPA is intermediate AND ySTD is intermediate, then activity is walking.

Rule 3: if SMA is high AND xPPA is high AND ySTD is high, then activity is running.

Rule 4: if SMA is high AND xPPA is intermediate AND ySTD is high, then activity is running.

2) *Database*

Database defines the membership functions (MFs) of inputs and outputs. A membership function is a curve which defines how each point in the input space is mapped to a membership value between 0 and 1.

In our system, MFs were designed based on the experimental data. We collected considerable acceleration data from 10 subjects when they are walking, running or at rest. The ranges of parameters are shown in TABLE 1. Using these data, membership functions were defined as shown in FIG. 4.

3) *Decision-Making Unit*

Decision-making unit performs the fuzzy operations on the rules. In our FIS, "min" is for AND operator while

"max" is for OR operator. We also use "min" for implication of each rule. Implication is the process of sharping the fuzzy set in the consequent based on the results of antecedent in a FIS.

4) *Fuzzification Interface*

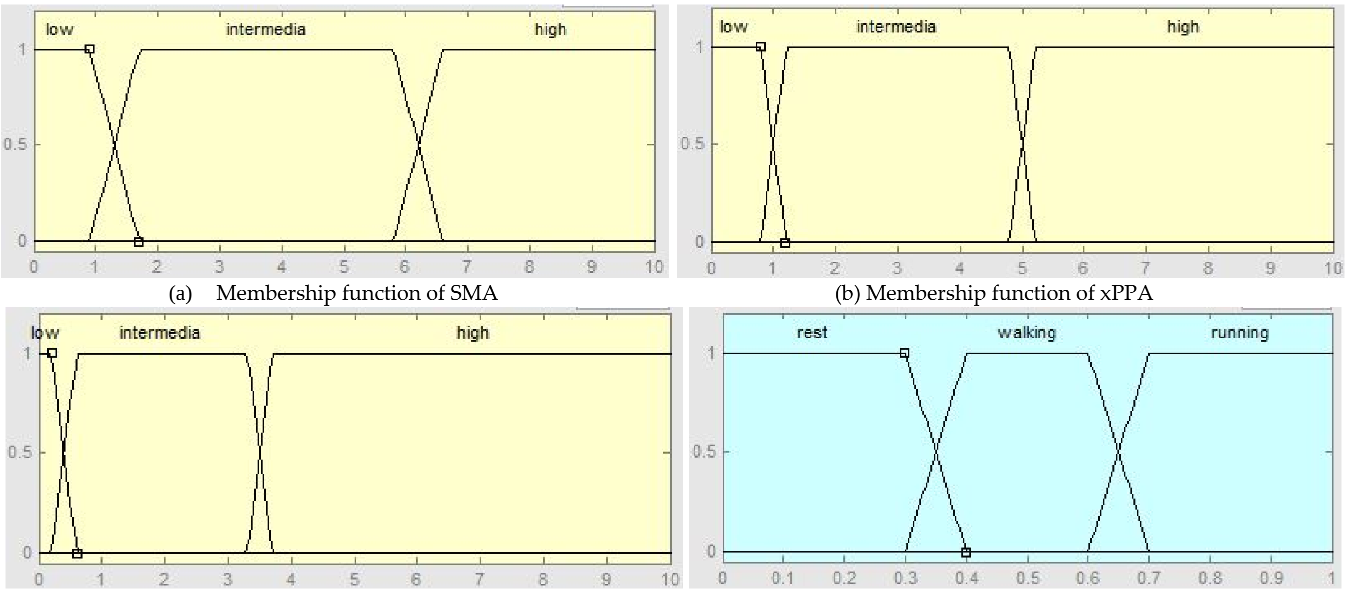
Fuzzification Interface takes the crisp inputs, then determines the degrees to the fuzzy sets using membership functions.

5) *Defuzzification Interface*

Aggregation is done in this part firstly. In our system, it combines the 4 outputs of fuzzy rules and forms a single fuzzy set, which is later used for a defuzzification method to determine the final crisp output. Here, "max" is used for aggregation. We choose the centroid calculation as the defuzzification method, which returns the center of area under the curve (Helmi et al.,2009).

TABLE 1 RANGE OF ACCELERATION PARAMETERS

	Rest	Walking	Running
SMA(m/s^2)	0.1246-0.4164	1.5674-4.0612	6.3664-8.2385
xPPA(m/s^2)	0.3472-0.7315	1.9267-6.5851	6.0449-8.5300
ySTD(m/s^2)	0.0729-0.1681	0.6896-2.5354	4.6387-6.2550



(a) Membership function of SMA (b) Membership function of xPPA

(c) Membership function of ySTD (d) Membership function of output(activity)

FIG. 4 MEMBERSHIP FUNCTIONS OF INPUTS (a), (b), (c) AND OUTPUT (d)

A usage of this FIS can be shown by applying an input vector [SMA xPPAySTD] to it. See FIG. 5, we apply the sample [3.594.882.01] to this FIS, the output is 0.5. TABLE 2 shows how the activity can be recognized using the crisp output. That is to say, 0.5 means walking.

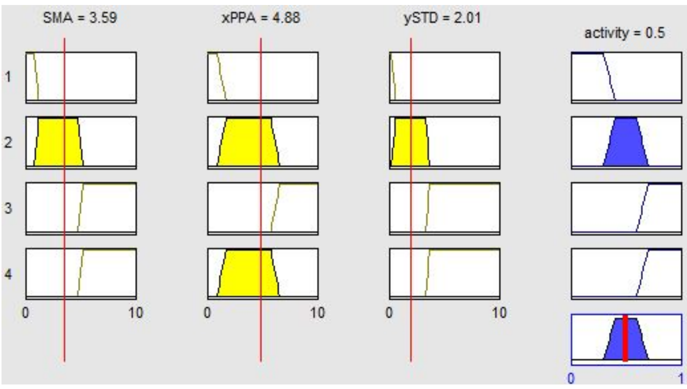
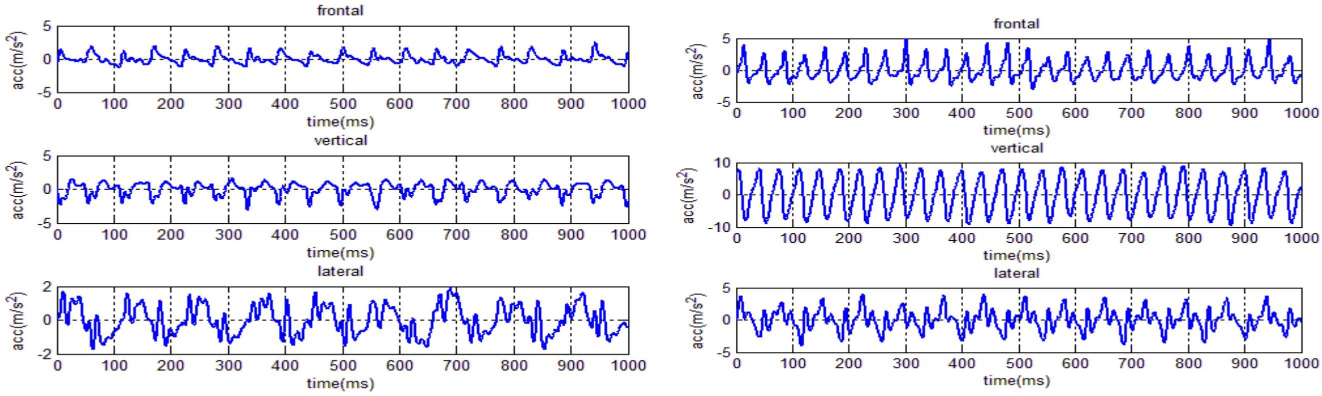


FIG. 5 RULE VIEW. INPUT: [3.59 4.88 2.01], OUTPUT: 0.5

TABLE 2 ACTIVITY RECOGNITION FROM THE CRISP OUTPUT

Crisp Output	Activity
0.00-0.35	Rest
0.35-0.65	Walking
0.65-1.00	Running



(a) Walking acceleration signal (b)Running acceleration signal

FIG. 6 TRI-AXIAL ACCELERATION SIGNALS OF WALKING AND RUNNING

Speed EstimationUsing Artificial Neural Networks

Theoretically, we can get speed of the subject by integrating acceleration once. However, using integration method a little sensor drift can be magnified, which makes it difficult to estimate speed precisely. It has been demonstrated that the use of artificial neural network techniques for decision making in certain gait analysis applications is more effective than biomechanical methods or conventional statistics. ANNs have been shown to be successful in finding complex relationships between patterns of different signals (Zhanga K. et al.,2005). In this paper, we built two three-layer BP ANNs, which were used for walking and running speed estimation respectively. Each ANN had 3 input units, 10 hidden units and 1 output unit.

FIG. 6 (a), (b) show tri-axial acceleration signals when the subject is walking and running. We can see the amplitude and shape of the signals' curve are of significant difference under these two conditions. Therefore, it's necessary to design two ANNs for walking and running respectively.

According to our experience, the frontal acceleration intensity is strongly correlated to walking and running speed. Thus, we used one step's peak to peak amplitude of frontal acceleration (xPPA) as one of the ANN's inputs. We also know that step frequency affect walking and running speed greatly, so we used duration of one step (DoS) as another input. Schutz Y. et al. (Schutz Y. et al.,2002) showed that the root mean square of the vertical acceleration (yRMS) is also an important factor to speed estimation, therefore we used yRMSas the third input of our ANNs. So far, our three input units were defined, and these inputs can be easilyobtained from the acceleration signal.

The structure of our BP ANN is shown in FIG. 7. To implementing the complex mapping from acceleration parameters to speed, tangsig function and purelin function were respectively selected as the transmission functions in the mid-layer and output-layer. The output of the ANN can be represented as follows:

$$O_{speed} = W_{out}\left[\frac{2}{1+e^{-2(W_{in}P+B_{in})}} - 1\right] + B_{out} \tag{4}$$

where P=$[p1\ p2\ p3]^T$ is the 3x1 input vector, W_{in} is the 10x3 weights matrix of hidden layer, W_{out} is the 1x10 weights matrix of output layer, B_{in} is the 10x1 threshold value vector of hidden layer, B_{out} is the 1x1 threshold value vector of output layer, O_{speed} is the 1x1 vector.

As the structure of ANN has been built, next we should train the weights and thresholds of the network. Levenberg-Marquardt (LM) algorithm was adopted as the training function. We used the gradient descent with momentum (GDM) as the learning function and the mean square error (MSE) as the perform function. MSE was minimized during the training process. The MSE equals the mean of the sum of the squares of the deviations from the target values, that is,

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(O_l - T_l)^2 \tag{5}$$

Where $O_l = l^{th}$ value of a group of n values of outputs, $T_l = l^{th}$ value of a group of n target values for the variable of interest (Zhanga K. et al.,2005). We trained the walking neutral network (WNN) and running neutral network (RNN) with 100 data across 5 recruited volunteers, then tested other 60 untrained data from another 3 volunteers. The result is shown in the next section.

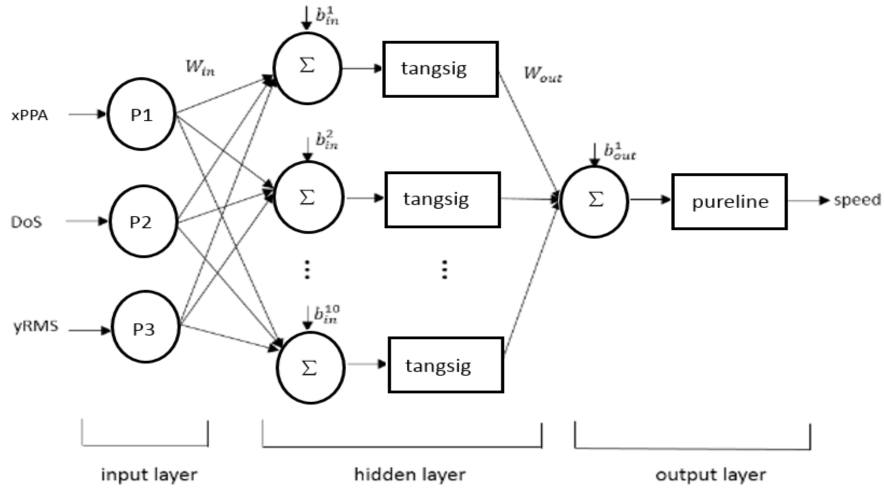


FIG. 7 STRUCTURE OF BP NEUTRAL NETWORK

TABLE 3 ACTIVITY RECOGNITION RATE

Activity	Recognition rate (%)
Rest	99.5
Walking	95.6
Running	98.3

ExperimentsAnd Results

As we designed a FIS to recognize human activity and ANNs to estimate speed of walking and running, two experiments were conducted to validate each system respectively.

Fuzzy Inference System

Three types of daily physical activities were collected with each type lasting for 5 minutes, which means each type was repeated many times. The three types of activity are rest, walking and running. All the activities were performed freely in the real-life environment by 10 recruited volunteers. The result is shown in TABLE 3.

The main error lies in the recognition of fast walking and slow running. It's a difficult problem existing in human activity recognition area for many years. Generally speaking, our FIS performs quite well with high recognition rates.

Artificial Neutral Networks

Training and testing data were all collected by recruited volunteers using treadmill which was set at different speed ranging from 1.5 km/h to 11.5 km/h. The result is shown in TABLE 4. The correlation between actual and estimated speed of walking and running is shown in FIG. 8. In the testing process, we collected 2 data sets of each subject independently at a fixed speed. As there were 3 subjects, the estimated speed was calculated using the following equation:

$$Estimated\ Speed = \frac{1}{3*2}\sum_{i=1}^{3}\sum_{j=1}^{2} v_i^j \tag{6}$$

Where v_i^j is subject- i's ANN output in experiment- j. The relative error is defined as:

$$Relative\ Error(\%) = \frac{|Estimated\ \ speed\ -Actual\ \ speed\ |}{Actual\ \ speed} * 100 \tag{7}$$

From the result, we can see that the maximum of walking-speed-estimation error and running-speed-estimation error are 6.00% and 6.56%, respectively. The average accuracy of speed estimation is 97.78% for walking and 97.36% for running. The correlation between actual and estimated speed is 0.9975, $p<0.0001$. The result shows that our approach is of great value in human walking and running speed estimation area with high accuracy and easy operating.

TABLE 4 WALKING AND RUNNING SPEED

Type of gait	Actual speed (km/h)	Estimated speed (km/h)	Relative error (%)
Walking	1.50	1.41	6.00
	2.00	1.97	1.50
	2.50	2.55	2.00
	3.00	2.82	6.00
	3.50	3.49	0.29
	4.00	4.13	3.25
	4.50	4.53	0.67
	5.00	4.94	1.20
	5.50	5.52	0.36
	6.00	5.83	2.83
	6.50	6.49	0.15
Running	7.00	7.15	2.14
	7.50	7.69	2.53
	8.00	8.12	1.50
	8.50	8.84	4.00
	9.00	9.59	6.56
	9.50	9.62	1.26
	10.00	9.97	0.30
	10.50	9.99	4.86
	11.00	10.71	2.64
	11.50	11.57	0.61

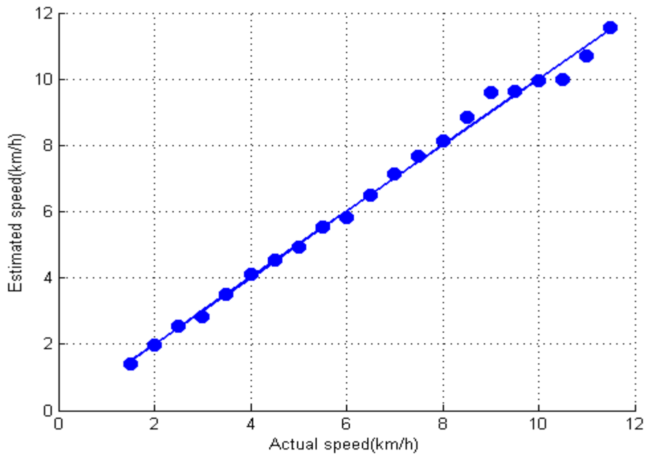


FIG. 8 CORRELATION BETWEEN ACTUAL AND ESTIMATED SPEED

Conclusions

This paper proposes a new approach to estimate walking and running speed using a wearable device based on a tri-axial accelerometer. First, a FIS is designed for human activity recognition. If the subject is locomotor, then two three-layer ANNs are applied for walking and running speed estimation respectively. We extract three parameters from the acceleration signal as the inputs of ANNs, namely one step's peak to peak amplitude of frontal acceleration, duration of one step, and the root mean square of vertical acceleration. After training and testing, our approach proves to be an effective method for speed estimation of walking and running, which can be used in many areas such as physical exercise, health evaluation and rehabilitation training.

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